TOA SW clear-sky fluxes for EarthCARE's BBR: towards a global and time-invariant radiance-to-flux converter

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Why EarthCARE? (launch in 2018)

- instrumental setup to retrieve aerosol and cloud properties in 3D
- simulate outgoing radiative fluxes and compare against **measurement-based fluxes** (radiative closure)
- assume good understanding of cloud-aerosol-radiance interaction for difference of < 10 W/m^2

http://www.esa.int/

Focus on clear-sky scenes

- homogeneous cases should pose little difficulties to radiative closure assessment
- for best cloud assessment in semi-transparent or broken cloud fields, ensure that cloud-free portions are handled well

▷ **optimize SW clear-sky radiance-to-flux conversion**

Why Broadband Radiometer (BBR)?

- measures radiances over **solar (SW)** and total (SW+thermal) broadband spectrum
- at three viewing angles: nadir, 55° for- & backward

Why do differently than CERES?

- BBR with reduced viewing geometry
- no MODIS-like data available
- simpler representation is desireable

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◁ The regression task & CERES ADMs

CERES SSF ADMs

- sev. years of SW radiance obs.
- over land surfaces
  - an ADM per calender month and regional bin (1°x1°)
  - per interval of TOA NDVI and elevation variability
- over ocean surfaces
  - an ADM per interval of 10m wind and AOD
  - angular bins (2° SZA, RAA, VZA)
- resulting in several 100 ADMs
- using MODIS-based products (not available in EarthCARE)

The regression task

- **measuring TOA SW radiance** with the BBR
- want to **predict TOA SW flux** (all radiance leaving through upward hemisphere)
  $F \sim I$
- problematic: surface and atmosphere contribute to TOA anisotropy
- ideally: have parameters providing information on a scene's anisotropic nature
- alternativly:
  find auxiliary variables explaining differences between CERES ADMs and use as input for regression (e.g. in ANN)
  $F = f(I, \ldots)$

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◁ Goals and limitations of this study

We aim for...

- a simpler representation of CERES ADMs without MODIS support
- on the other hand, new auxiliary data will be needed (we want to find out which ones are essential)
- to establish and optimize radiance-to-flux conversion (e.g. using Artificial Neural Networks as regression tool)

Limitations

- three EarthCARE BBR viewing direction (nadir, 55° for- & backward)
- CERES footprints of pure IGBP type (66% of all clear-sky observations, 4 Mio. samples)

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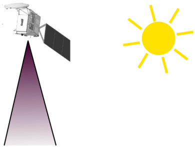

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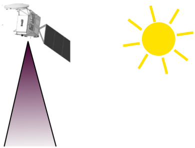
- **output: TOA SW Flux** (estimated in CERES SSF Edition 4)

▷ **find the essential parameter subset** for optimal radiance-to-flux conversion using Artificial Neural Networks

◁ Extracted geophysical parameters



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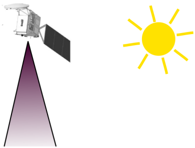

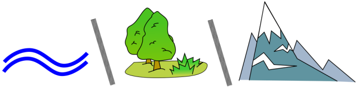

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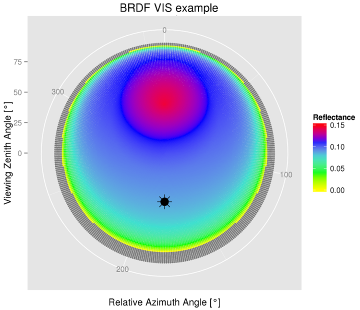

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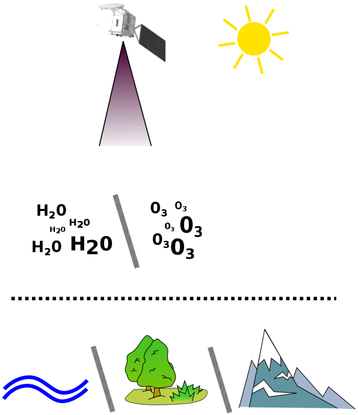

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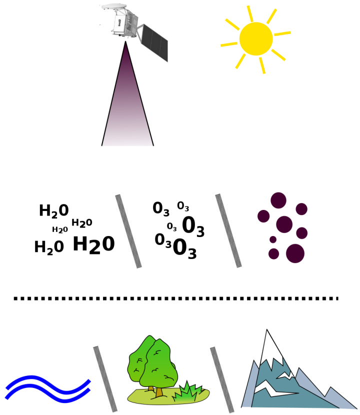

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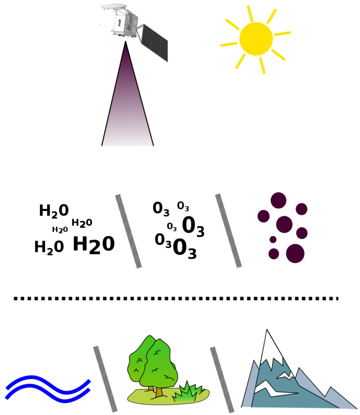

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Variable importance metrics

Random Forest Regression

- multiple decision trees
- use of aux. data for split nodes
- at each leaf (each end of a tree):

$$F \sim I + I^2 \mid w_{10m}, AOD, \ldots$$

- permutation test measures importance of each aux. variable

Linear Model with Genetic Algorithms

- using aux. data as direct proxy for anisotropy
- search algorithm determines best aux. data subset

$$F \sim I(w_{10m} + \ldots) + I^2(\ldots)$$

Surface Types

	Permanent Snow			Desert			Open Water		
Scattering	B	F	N	B	F	N	B	F	N
SZA	●	●	●	●	●	●	●	●	●
VZA		●				●	●	●	●
RAA	●	●	/	●	●	/	●	●	/
P(SGA)	●	●	●	●	●	●	●	●	●
Hotspot	●	●	●	●	●	●	●	●	●
AeroCom Median AOD	●	●	●	●	●	●	●	●	●
ERA Ozone	●	●	●	●	●				
ERA TCWV	●	●	●			●	●		●
A_{surf} Black-sky VIS	●	●	●	●	●	●	/	/	/
A_{surf} Black-sky NIR	●	●	●	●	●	●	/	/	/
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ERA LAI low veg.	/	/	/				/	/	/
ERA LAI high veg.	/	/	/		●	●	/	/	/
ERA 10m wind		●		●		●		●	●
ERA surface roughn.	●	●	●	●		●		●	●
ERA charnock		●	●		●	●			●
ERA snow depth	●		●	/	/	/	/	/	/
ERA snow albedo	●			/	/	/	/	/	/
ERA snow density	●		●	/	/	/	/	/	/

Observations

- inclusion of:
  - aux. variables related to viewing and illumination geometry
  - AOD
  - land surface BRDF and albedo
- exclusion of:
  - most ERA surface parameters
- uncertain about:
  - ERA ozone & TCWV
  - ERA 10m wind

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Linear Model	Y	N
Y	●	
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Scattering	B	F	N	B	F	N	B	F	N
SZA	●	●	●	●	●	●	●	●	●
VZA		●				●	●	●	●
RAA	●	●	/	●	●	/	●	●	/
P(SGA)	●	●	●	●	●	●	●	●	●
Hotspot	●	●	●	●	●	●	●	●	●
AeroCom Median AOD	●	●	●	●	●	●	●	●	●
ERA Ozone	●	●	●	●	●				
ERA TCWV	●	●	●			●	●		●
A_{surf} Black-sky VIS	●	●	●	●	●	●	/	/	/
A_{surf} Black-sky NIR	●	●	●	●	●	●	/	/	/
A_{surf} White-sky VIS	●	●	●	●	●	●	/	/	/
A_{surf} White-sky NIR	●	●	●	●	●	●	/	/	/
α_{surf} Black-sky VIS	●	●	●	●	●	●	/	/	/
α_{surf} White-sky VIS	●	●	●	●	●	●	/	/	/
α_{surf} Black-sky NIR	●	●	●	●	●	●	/	/	/
α_{surf} White-sky NIR	●	●	●	●	●	●	/	/	/
ERA LAI low veg.	/	/	/				/	/	/
ERA LAI high veg.	/	/	/		●	●	/	/	/
ERA 10m wind		●		●		●		●	●
ERA surface roughn.	●	●	●	●		●		●	●
ERA charnock		●	●		●	●			●
ERA snow depth	●		●	/	/	/	/	/	/
ERA snow albedo	●			/	/	/	/	/	/
ERA snow density	●		●	/	/	/	/	/	/

Observations

- inclusion of:
  - aux. variables related to viewing and illumination geometry
  - AOD
  - land surface BRDF and albedo
- exclusion of:
  - most ERA surface parameters
- uncertain about:
  - ERA ozone & TCWV
  - ERA 10m wind

		Random Forest	
		Y	N
Linear Model	Y	●	
	N	●	●

Variable importance metrics

Random Forest Regression

- multiple decision trees
- use of aux. data for split nodes
- at each leaf (each end of a tree):

$$F \sim I + I^2 \mid w_{10m}, AOD, \ldots$$

- permutation test measures importance of each aux. variable

Linear Model with Genetic Algorithms

- using aux. data as direct proxy for anisotropy
- search algorithm determines best aux. data subset

$$F \sim I(w_{10m} + \ldots) + I^2(\ldots)$$

	Surface Types								
	Permanent Snow			*Desert*			*Open Water*		
Scattering	B	F	N	B	F	N	B	F	N
SZA	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢
VZA		🟡				🟡	🟢	🟢	🟡
RAA	🟢	🟢	/	🟢	🟢	/	🟢	🟢	/
P(SGA)	🟢	🟢	🟢	🟢	⚫	🟢	🟢	🟢	🟢
Hotspot	🟢	🟢	⚫	🟢	🟢	🟢	🟢	🟢	🟢
AeroCom Median AOD	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢
ERA Ozone	⚫	🟢	🟢	⚫	🟢				
ERA TCWV	🟢	🟢	⚫			🟡	🟡		🟡
A_{surf} Black-sky VIS	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
A_{surf} Black-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
A_{surf} White-sky VIS	🟢	🟢	🟢	🟢	⚫	⚫	/	/	/
A_{surf} White-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} Black-sky VIS	🟢	🟢	🟢	🟢	🟢	⚫	/	/	/
α_{surf} White-sky VIS	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} Black-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} White-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
ERA LAI low veg.	/	/	/				/	/	/
ERA LAI high veg.	/	/	/		🟡	🟡	/	/	/
ERA 10m wind		🟢		🟢		🟡		🟢	🟢
ERA surface roughn.	🟡	🟡	🟡	🟡		🟡		🟢	⚫
ERA charnock		🟡	🟡		🟡	🟡			🟡
ERA snow depth	🟡		🟡	/	/	/	/	/	/
ERA snow albedo	🟡			/	/	/	/	/	/
ERA snow density	🟡		🟡	/	/	/	/	/	/

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Linear Model	Y	🟢	
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RAA	🟢	🟢	/	🟢	🟢	/	🟢	🟢	/
P(SGA)	🟢	🟢	🟢	🟢	⚫	🟢	🟢	🟢	🟢
Hotspot	🟢	🟢	⚫	🟢	🟢	🟢	🟢	🟢	🟢
AeroCom Median AOD	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢
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A_{surf} White-sky VIS	🟢	🟢	🟢	🟢	⚫	⚫	/	/	/
A_{surf} White-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} Black-sky VIS	🟢	🟢	🟢	🟢	🟢	⚫	/	/	/
α_{surf} White-sky VIS	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} Black-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} White-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
ERA LAI low veg.	/	/	/				/	/	/
ERA LAI high veg.	/	/	/		🟡	🟡	/	/	/
ERA 10m wind		🟢		🟢		🟡		🟢	🟢
ERA surface roughn.	🟡	🟡	🟡	🟡		🟡		🟢	⚫
ERA charnock		🟡	🟡		🟡	🟡			🟡
ERA snow depth	🟡		🟡	/	/	/	/	/	/
ERA snow albedo	🟡			/	/	/	/	/	/
ERA snow density	🟡		🟡	/	/	/	/	/	/

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Linear Model \ Random Forest	Y	N
Y	🟢	
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VZA		🟡				🟡	🟢	🟢	🟡
RAA	🟢	🟢	/	🟢	🟢	/	🟢	🟢	/
P(SGA)	🟢	🟢	🟢	🟢	⚫	🟢	🟢	🟢	🟢
Hotspot	🟢	🟢	⚫	🟢	🟢	🟢	🟢	🟢	🟢
AeroCom Median AOD	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢	🟢
ERA Ozone	⚫	🟢	🟢	⚫	🟢				
ERA TCWV	🟢	🟢	⚫			🟡	🟡		🟡
A_{surf} Black-sky VIS	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
A_{surf} Black-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
A_{surf} White-sky VIS	🟢	🟢	🟢	🟢	⚫	⚫	/	/	/
A_{surf} White-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} Black-sky VIS	🟢	🟢	🟢	🟢	🟢	⚫	/	/	/
α_{surf} White-sky VIS	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} Black-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
α_{surf} White-sky NIR	🟢	🟢	🟢	🟢	🟢	🟢	/	/	/
ERA LAI low veg.	/	/	/				/	/	/
ERA LAI high veg.	/	/	/		🟡	🟡	/	/	/
ERA 10m wind		🟢		🟢		🟡		🟢	🟢
ERA surface roughn.	🟡	🟡	🟡	🟡		🟡		🟢	⚫
ERA charnock		🟡	🟡		🟡	🟡			🟡
ERA snow depth	🟡		🟡	/	/	/	/	/	/
ERA snow albedo	🟡			/	/	/	/	/	/
ERA snow density	🟡		🟡	/	/	/	/	/	/

Observations

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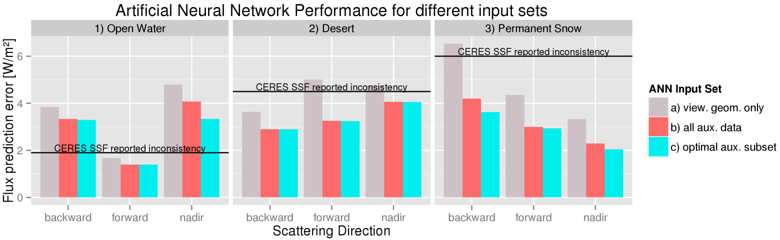
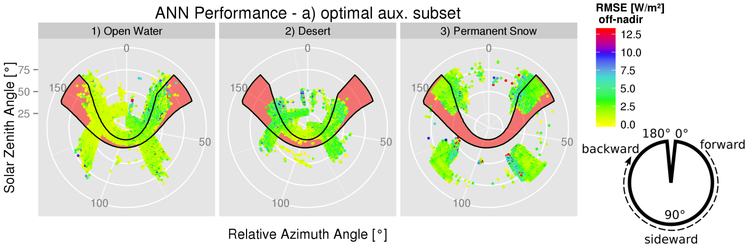
Linear Model \ Random Forest	Y	N
Y	🟢	
N	⚫	🟡

Optimization of ANNs for rad-to-flux conversion



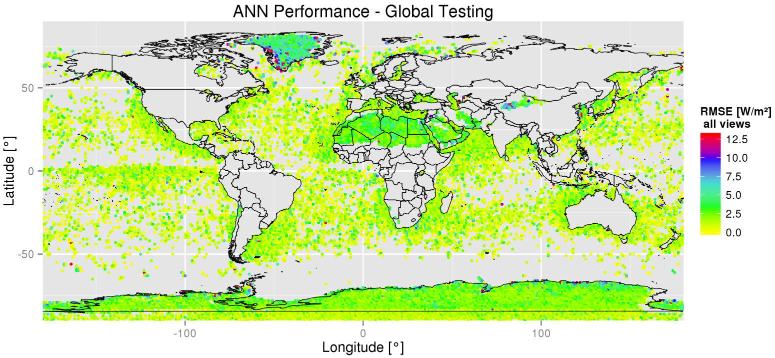
- optimal subset of aux. data with best performance on predicting CERES fluxes

Optimization of ANNs for rad-to-flux conversion



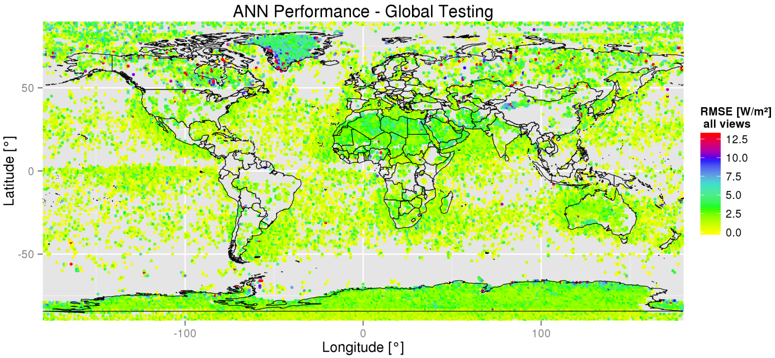
- satisfying performance for EarthCARE-like geometry (red shaded area)

Optimization of ANNs for rad-to-flux conversion



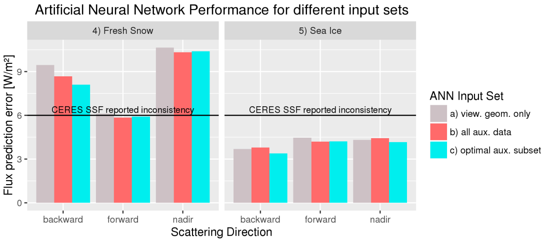
- overall good performance, except for very mountainous terrain

Optimization of ANNs for rad-to-flux conversion



- similarly high perf. for other sfc. types, except for *Fresh Snow*

Uncertainty over Fresh Snow

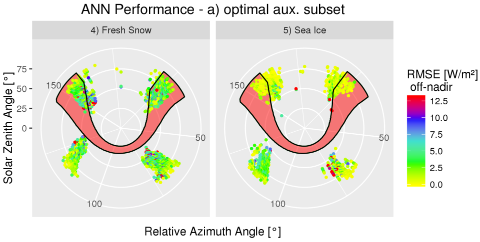


- above CERES inconsistencies

Surface Types

Scattering	Fresh Snow B	Fresh Snow F	Fresh Snow N	Sea Ice B	Sea Ice F	Sea Ice N
SZA	•	•	•	•	•	•
VZA			•	•	•	
RAA	•	•	/	•	•	/
P(SGA)	•	•	•		•	•
Hotspot	•	•	•	•	•	•
AeroCom Median AOD	•		•	•		•
ERA Ozone		•	•	•	•	•
ERA TCWV				•	•	•
A_{surf} Black-sky VIS	•	•	•	/	/	/
A_{surf} Black-sky NIR	•	•	•	/	/	/
A_{surf} White-sky VIS	•	•	•	/	/	/
A_{surf} White-sky NIR	•	•	•	/	/	/
α_{surf} Black-sky VIS	•	•	•	/	/	/
α_{surf} White-sky VIS	•	•	•	/	/	/
α_{surf} Black-sky NIR	•		•	/	/	/
α_{surf} White-sky NIR	•			/	/	/
ERA LAI low veg.		•	•	/	/	/
ERA LAI high veg.	•		•	/	/	/
ERA 10m wind				•		•
ERA surface roughn.	•		•	•	•	•
ERA charnock	•	•		•		•
ERA snow depth	•		•	/	/	/
ERA snow albedo	•		•	/	/	/
ERA snow density	•	•	•	/	/	/
ERA ice cover	/	/	/	•	•	•

Uncertainty over Fresh Snow

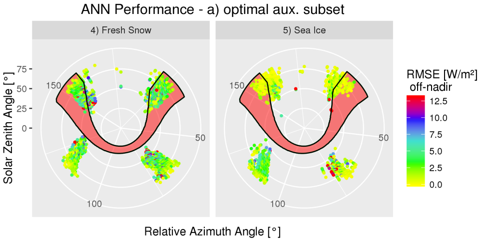


- for non-EarthCARE geometries

Surface Types

	Fresh Snow			Sea Ice		
Scattering	B	F	N	B	F	N
SZA	•	•	•	•	•	•
VZA			•	•	•	
RAA	•	•	/	•	•	/
P(SGA)	•	•	•		•	•
Hotspot	•	•	•	•	•	•
AeroCom Median AOD	•		•	•		•
ERA Ozone		•	•	•	•	•
ERA TCWV				•	•	•
A_{surf} Black-sky VIS	•	•	•	/	/	/
A_{surf} Black-sky NIR	•	•	•	/	/	/
A_{surf} White-sky VIS	•	•	•	/	/	/
A_{surf} White-sky NIR	•	•	•	/	/	/
α_{surf} Black-sky VIS	•	•	•	/	/	/
α_{surf} White-sky VIS	•	•	•	/	/	/
α_{surf} Black-sky NIR	•		•	/	/	/
α_{surf} White-sky NIR	•			/	/	/
ERA LAI low veg.		•	•	/	/	/
ERA LAI high veg.	•		•	/	/	/
ERA 10m wind				•		•
ERA surface roughn.	•		•	•	•	•
ERA charnock	•	•		•		•
ERA snow depth	•		•	/	/	/
ERA snow albedo	•		•	/	/	/
ERA snow density	•	•	•	/	/	/
ERA ice cover	/	/	/	•	•	•

Uncertainty over Fresh Snow



- uncertainty refl. in parameter choice

	Surface Types					
	Fresh Snow			*Sea Ice*		
Scattering	B	F	N	B	F	N
SZA	●	●	●	●	●	●
VZA			●	●	●	
RAA	●	●	/	●	●	/
P(SGA)	●	●	●		●	●
Hotspot	●	●	●	●	●	●
AeroCom Median AOD	●		●	●		●
ERA Ozone		●	●	●	●	●
ERA TCWV				●	●	●
A_{surf} Black-sky VIS	●	●	●	/	/	/
A_{surf} Black-sky NIR	●	●	●	/	/	/
A_{surf} White-sky VIS	●	●	●	/	/	/
A_{surf} White-sky NIR	●	●	●	/	/	/
α_{surf} Black-sky VIS	●	●	●	/	/	/
α_{surf} White-sky VIS	●	●	●	/	/	/
α_{surf} Black-sky NIR	●		●	/	/	/
α_{surf} White-sky NIR	●			/	/	/
ERA LAI low veg.		●	●	/	/	/
ERA LAI high veg.	●		●	/	/	/
ERA 10m wind				●		●
ERA surface roughn.	●		●	●	●	●
ERA charnock	●	●		●		●
ERA snow depth	●		●	/	/	/
ERA snow albedo	●		●	/	/	/
ERA snow density	●	●	●	/	/	/
ERA ice cover	/	/	/	●	●	●

◁ Wrap up...

In summary...

+ for TOA SW clear-sky rad-to-flux conversion in EarthCARE
  - aimed for a simpler representation of ADMs from CERES SSF
  - instead of MODIS, use of different auxiliary variables
  - found optimal subset of those variables
    - viewing and illumination geometry
    - land surface BRDFs and albedi
    - AOD, and partly total column O_3 and H_2O, as well as 10m wind
  - optimized performance of Artificial Neural Networks (uncertainty of 2.9-3.8 W/m^2)

Discussion

- Why are certain aux. variables important for the radiance-to-flux conversion?
  - Could aerosols or atm. gases serve as *anisotropy softener* ?
  - Does 10m wind change the structure of (some) land surfaces ?
  - Or do some variables simply serve to discriminate regionally ?

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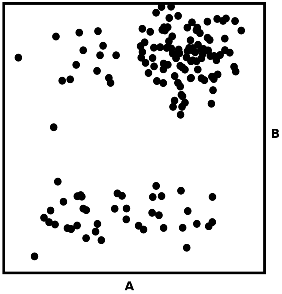
◁ Random Forest [Breiman, 2001]

- ensemble learning method for classification and regression
- multitude of decision trees
- therefore, correct for DT's tendency to overfit
- for regression: multi-dimensional step-function (each leaf with constant value) **or** continuous (each leaf with Linear Regression model)

◁ Random Forest [Breiman, 2001]



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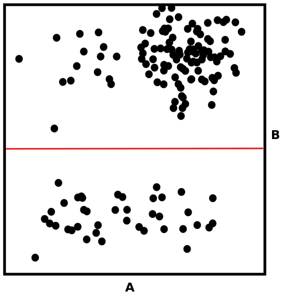
◁ Random Forest [Breiman, 2001]



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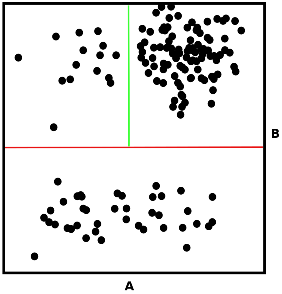

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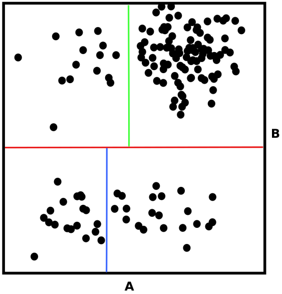

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◁ Identifying a subset through Random Forest Regression (not shown)

- train a multitude of **decision trees** with simple linear model at each leaf ($F \sim I + I^2$)
- aux. parameters serve to create special cases of radiance-to-flux conversion
- each split via *recursive partitioning:*
  - test several parameters
  - if and where to split to improve
  - only relevant parameters used
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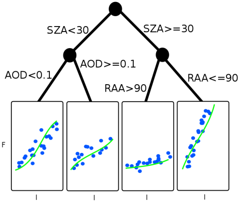

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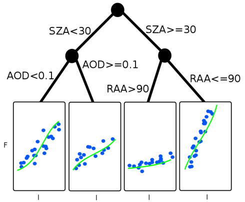

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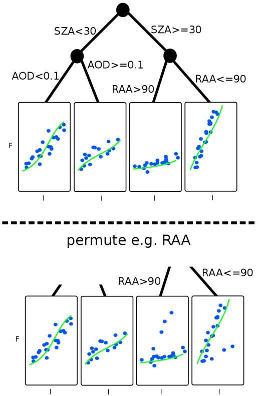


◁ Genetic Algorithms [Scrucca, 2009]

- simulate living organisms and their biological evolution (mutation, crossover, seletion & elitism)
- successfully applied to search & optimization problems

▷ procedure:

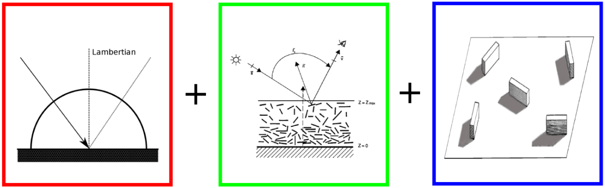
- randomly generate population of individuals (aka. strings or chromosomes)
- consisting of units (aka. genes, features or characters; i.e. 0/1)
- each genotype represents a solution to the optimiz. problem
- **fitness** evaluates closeness to optimization (here: BIC)
- exploration: creating population diversity (mutation & crossover)
- exploitation: reducing diversity by selecting fitter individuals

$$BIC = -2 \cdot \ln \left(\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \right) + k \cdot \ln (n)$$

with n observations and k parameters estimating $\hat{y}_i$

◁ Semi-empirical BRF - **Ross-Li**

$$R(\theta_s, \theta_o, \phi, \Lambda) = f_{iso}(\Lambda) + f_{vol}(\Lambda) \cdot K_{vol}(\theta_s, \theta_o, \phi) + f_{geo}(\Lambda) \cdot K_{geo}(\theta_s, \theta_o, \phi)$$



Adapted from Petty (2006) and Roujean et al. (1992)

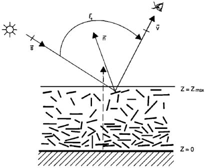
◁ $K_{vol}(\theta_s, \theta_o, \phi)$ - *Ross-Thick* Kernel

$$K_{vol}(\theta_s, \theta_o, \phi) = \frac{(\pi/2 - \zeta)\cos\zeta + \sin\zeta}{\cos\theta_s + \cos\theta_o} - \frac{\pi}{4}$$

with

$$\cos\zeta = \cos\theta_s \cos\theta_o + \sin\theta_s \sin\theta_o \sin\phi$$

- ▷ for large LAI-values ("**thick**") with small gaps in between leafs
- ▷ leaf facets uniformly oriented
- ▷ equal transmittance and reflectance of leafs
- ▷ above flat, Lambertian surface



Roujean et al., 1992

◁ $K_{geo}(\theta_s, \theta_o, \phi)$ - geometric-optical *Li-Sparse* Kernel

$$K_{geo}(\theta_s, \theta_o, \phi) = \frac{m}{\pi}(t - \sin t \cos t - \pi) + \frac{1 + \cos\zeta}{2\cos\theta_s \cos\theta_o}$$

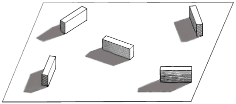
with

$$\cos t = \frac{2}{m}\sqrt{\Delta^2 + (\tan\theta_s \tan\theta_o \sin\phi)^2}$$

$$m = 1/\cos\theta_s + 1/\cos\theta_o$$

$$\Delta = \sqrt{\tan^2\theta_s + \tan^2\theta_o - 2\tan\theta_s \tan\theta_o \cos\phi}$$

- "**sparse**" spacing of objects (e.g. trees)
- randomly located spheriods with presumed 3D proportions
- ratio of sunlit/shaded crown and ground



Roujean et al., 1992

◁ Surface albedo

- ▷ ratio between hemispherical upwelling and downwelling radiative fluxes
- ▷ classic subdivision into:

black-sky albedo $\alpha_{bs} = \alpha_{bs}(\theta_s, \Lambda)$

- ▷ single-beam irradiation
- ▷ directional-hemisph. integral
- ▷ function of solar zenith angle

white-sky albedo $\alpha_{ws} = \alpha_{ws}(\Lambda)$

- ▷ perfectly diffuse illumination in turbid atmosphere
- ▷ independent from SZA

- ▷ diffuse illumination $S = S(\tau(\Lambda), \theta_s)$ determines albedo

$$\alpha = (1 - S) \cdot \alpha_{bs} + S \cdot \alpha_{ws} = \alpha(\theta_s, \Lambda, \tau(\Lambda))$$

◁ Albedo-derivation from BRF (Lucht and Schaaf, 2000)

- directional-hemispherical integral

$$h_k(\theta_s) = \frac{1}{\pi} \int_0^{2\pi} \int_0^{\pi/2} K_k(\theta_s, \theta_o, \phi) \sin\theta_o \cos\theta_o d\theta_o d\phi = \sum_j g_{jk} P_j(\theta_s)$$

$$\alpha_{bs}(\theta_s, \Lambda) = \sum_k f_k(\Lambda) h_k(\theta_s) = \sum_k f_k(\Lambda) \sum_j g_{jk} P_j(\theta_s)$$

- bihemispherical integral

$$H_k = 2 \int_0^{\pi/2} h_k(\theta_s) \sin\theta_s \cos\theta_s d\theta_s$$

$$\alpha_{ws}(\Lambda) = \sum_k f_k(\Lambda) H_k$$

▷ g_{jk}, $P_j(\theta_s)$ and H_k precomp., $f_k(\Lambda)$ obs.-based, $S(\tau(\Lambda), \theta_s)$ atm. state

◁ The MOD43B Level 3 product

- ▷ 7 channels in the visible (460, 555, 659nm) and near-infrared (865, 1240, 1640, 2130nm), as well as BB (VIS, NIR, total SW)
- ▷ 1km spatial and 16-day temporal resolution
- ▷ combination of Terra/Aqua MODIS and MISR to provide better angular sampling

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- ▷ MOD43B1
  - atmospherically corrected reflectances
  - RossLi BRF model parameters ($f_k(\Lambda)$)
- ▷ MOD43B2
  - parameters of empirical model (Walthall)
- ▷ MOD43B3
  - black- and white-sky albedos at local noon SZA
- ▷ MOD43B4
  - nadir-view reflectances for local median SZA

- ▷ along with several quality flags (snow,water,low sample number,...)

◁ ERA 20C reanalysis

- first atm. reanalysis of the 20th century (1900-2010)

- produced with IFS version Cy38r1
- coupled Atmosphere/Land-surface/Ocean-waves model
- assimilation of surface pressure and surface marine winds only

- 91 vertical levels, 4 soil layers
- $\sim$125km horiz. resolution (T159)
- ocean waves on 25 frequencies, 12 directions
- 3-hourly temp. resolution

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◁ Literature: Angular Distribution Models

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[Petty, 2006]
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◁ Linear Regression

- **in general** we want to derive an *intelligent* machine which can predict a value for us

- **we believe:**
  - that X has a connection to y
  - to understand the *world* with this model
- derive $\hat{w}$ from *Least Squares Estimate* [$\hat{w} = (X^T X)^{-1} X^T y$]
- **a common quality measure** is the *Residual Sum of Squares* (RSS):

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$$RSS = \sum_{i=1}^{N} (y - \hat{y})^2 = \sum_{i=1}^{N} (y - \hat{w}x)^2$$

◁ Challenges

- **How complex** should our model be?
- **Which features** should be in it?
- Do I need **more data** and/or **more features**?

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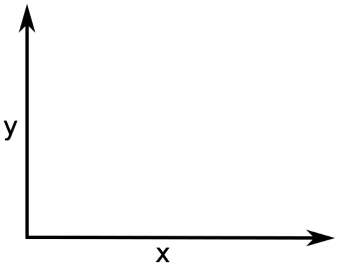

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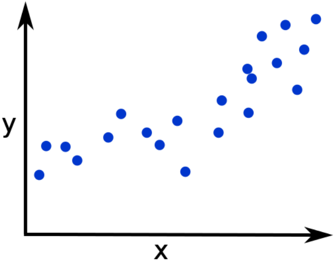

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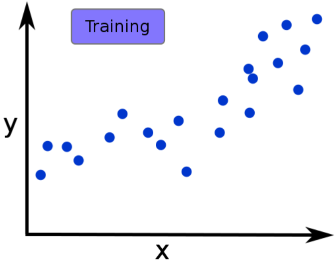

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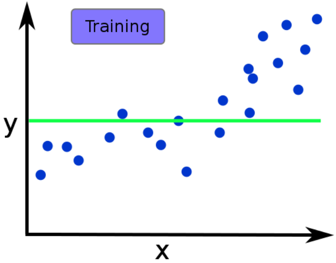

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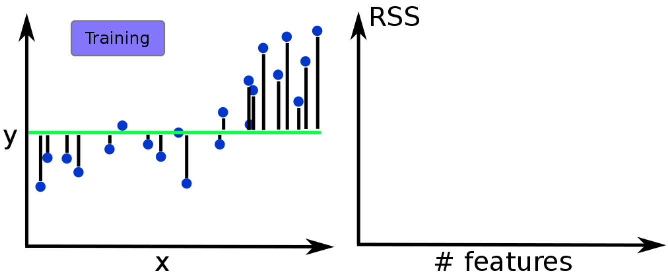

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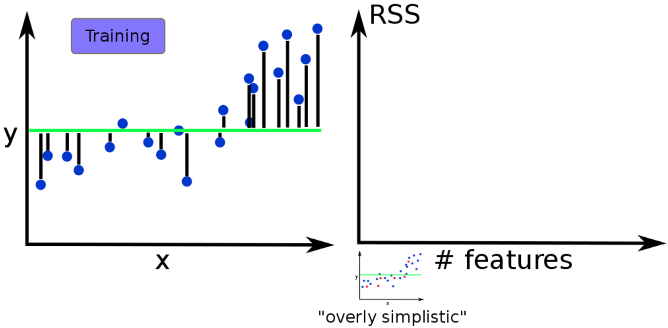

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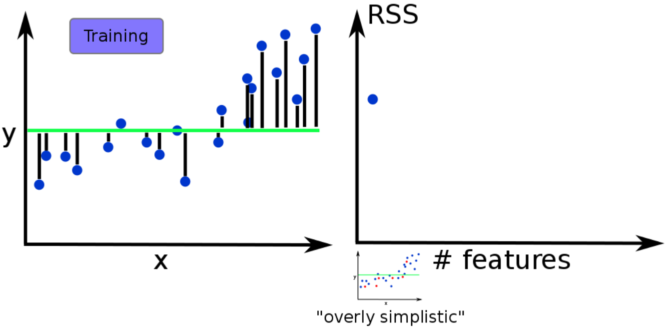

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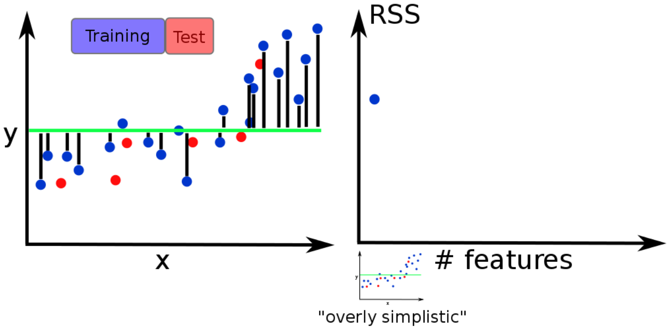

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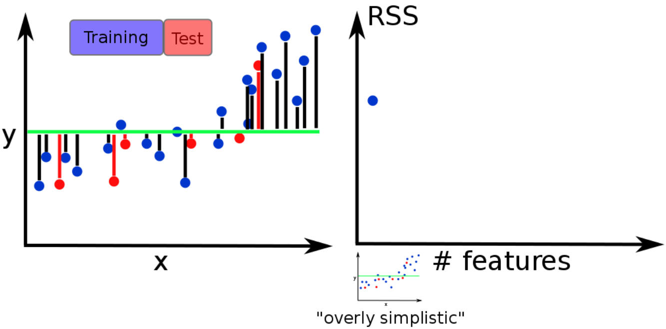

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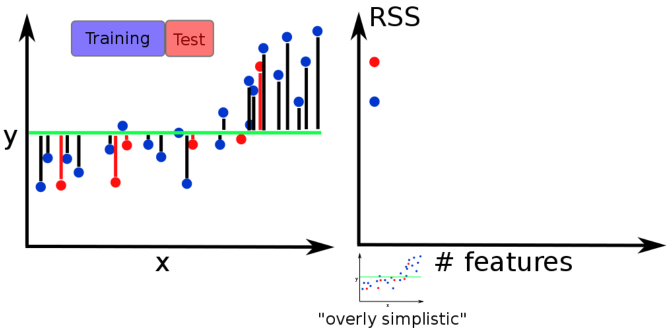

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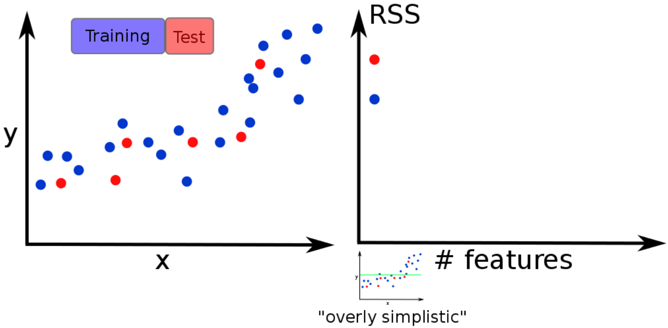

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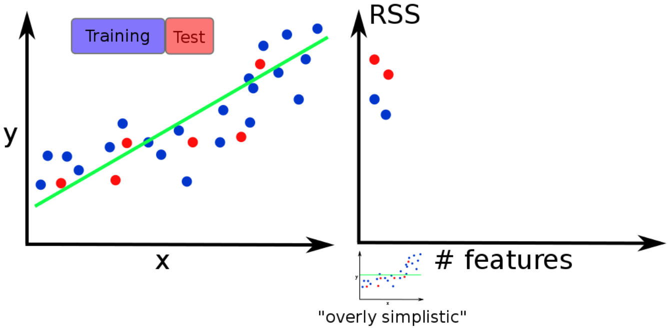

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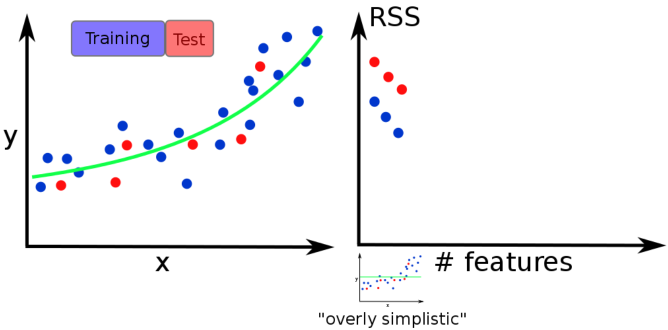

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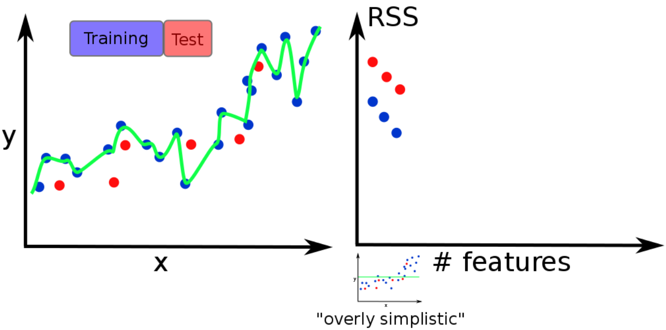

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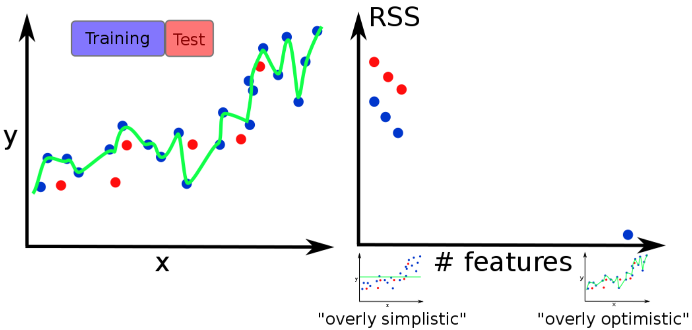

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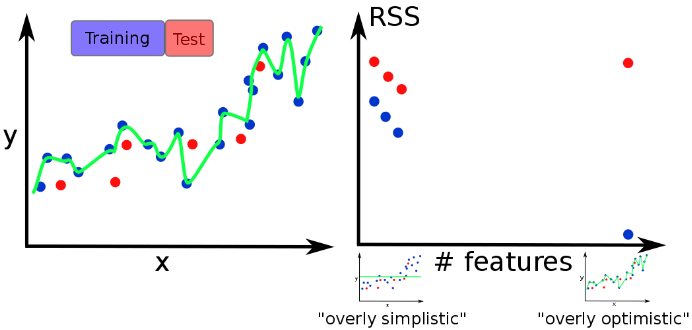

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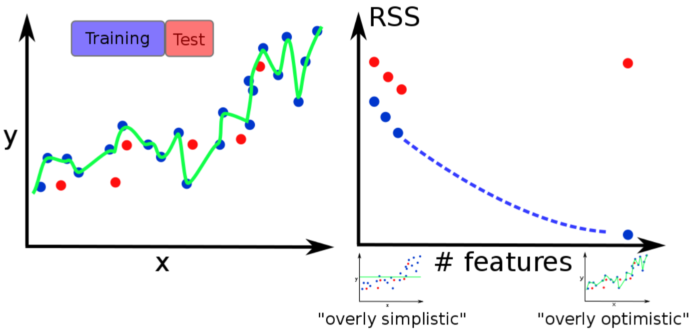

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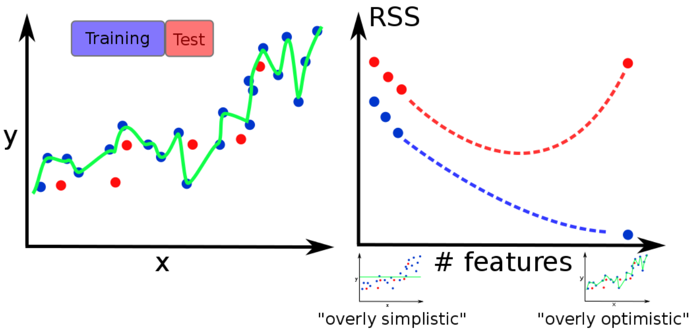

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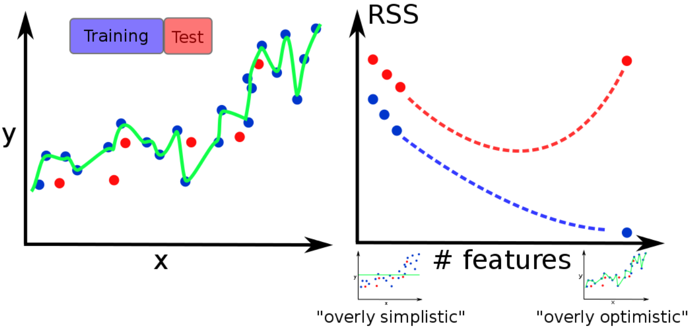

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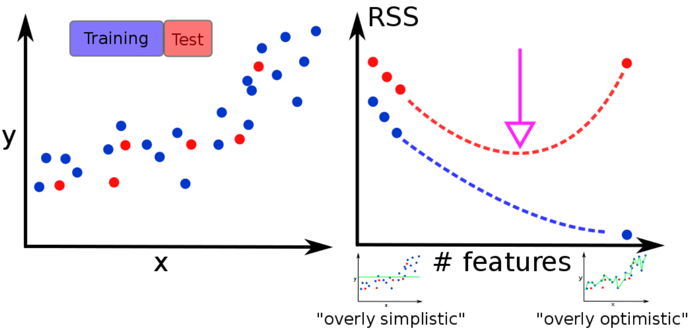

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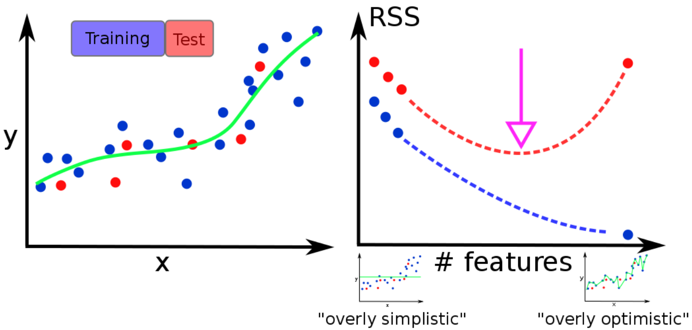

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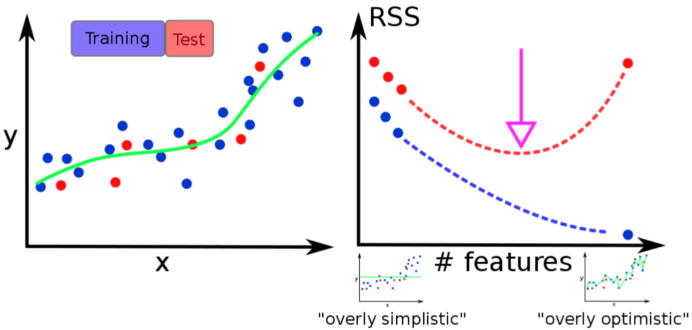

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    - *selection, crossover, mutation, elitsm*

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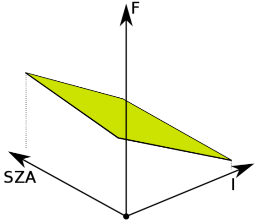

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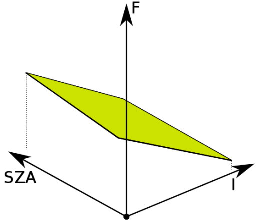

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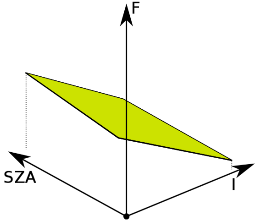

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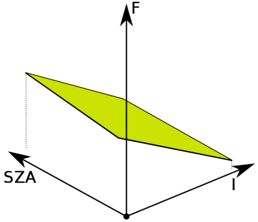

round N	round N+1
00100110100110 10110000101110	10110000101110

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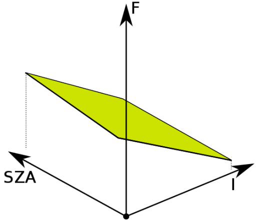

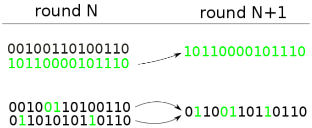

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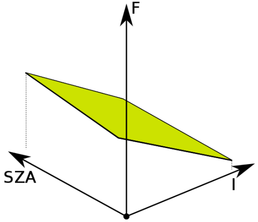

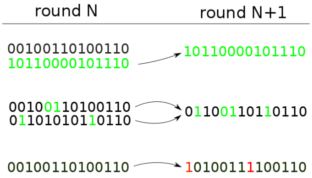

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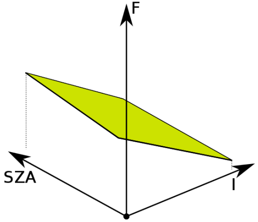

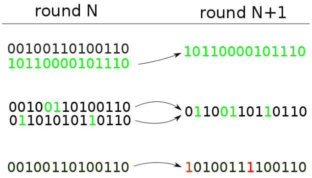

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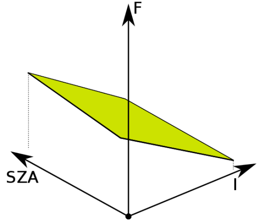
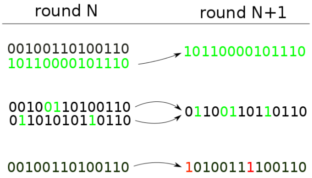
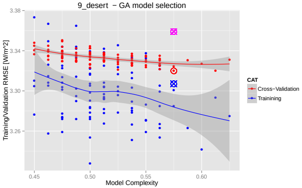




◁ Feature selection



- repeat Genetic Selection 100 times
- pick feature subset with lowest cross-validation error

Overview of slides

Talk

Appendix